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Objective measures, sensors and computational techniques for stress recognition and classification: A survey

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ABSTRACT

Stress is a major growing concern in our day and age adversely impacting both individuals and society. Stress research has a wide range of benefits from improving personal operations, learning, and increasing work productivity to benefiting society – making it an interesting and socially beneficial area of research. This survey reviews sensors that have been used to measure stress and investigates techniques for modelling stress. It discusses non-invasive and unobtrusive sensors for measuring *computed stress*, a term we coin in the paper. Sensors that do not impede everyday activities that could be used by those who would like to monitor stress levels on a regular basis (e.g. vehicle drivers, patients with illnesses linked to stress) is the focus of the discussion. Computational techniques have the capacity to determine optimal sensor fusion and automate data analysis for stress recognition and classification. Several computational techniques have been developed to model stress based on techniques such as Bayesian networks, artificial neural networks, and support vector machines, which this survey investigates. The survey concludes with a summary and provides possible directions for further computational stress research.

1. Introduction

There are escalating changes in technology and society, which bring growing demands for better techniques in dealing with wellbeing by containing everyday unavoidable life pressures and challenges. Stress is the leading threat to people because these daily demands cannot be satisfactorily handled, and is a risk to health and social aspects of life. The term, *stress*, introduced by Selye, defined stress as "the non-specific response of the body to any demand for change". In general, stress is a "complex reaction pattern that often has psychological, cognitive and behavioural components" [1]. It can essentially be used to describe the wear and tear of the body experiencing changing environments, thus giving three main facets – input stimulus, processing and evaluation, and response [2].

It has been widely accepted that stress, when sufficiently powerful so that it overcomes defence mechanisms, has a range of severe impacts on immune and cardiovascular systems on individuals. As stress becomes chronic, it makes individuals more vulnerable to infections and incurable diseases, and slows down the body's recovery processes [3]. In addition, stress causes financial burdens on society [4]. There are organisations (e.g. International Stress Management Association UK [5], SupportLine [6] and Lifeline Australia [7]) in place to help individuals deal with stress and in creating awareness of the issues associated with stress, a major problem faced by the world today.

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Various response (or symptom) measures have been used to interpret stress levels and fluctuations. The response measures reflect reactions of individuals and their body to stressful situations. Some individuals may react differently to stressful events from others due to their body conditions, age, gender, experience and so on. There are computational techniques, such as artificial neural networks, that can deal with these variables [8]. Additionally, uncertainties and complexities also exist that need to be dealt with when defining stress. Techniques such as, fuzzy logic, can narrow the gap.

Hormonal imbalances and physiological and physical changes are some characteristics associated with stress, i.e. they are symptoms of stress. When a person is under stress, increased amounts of stress hormones (e.g. cortisol or catecholamine levels) are released and measures for these hormones are obtained via invasive methods (e.g. taking blood, saliva or urine samples), possibly performed by qualified practitioners, and require lengthy analysis procedures conducted by qualified scientists ([9–12]). Also under stress, changes in heart rate (HR) [13], blood pressure (BP) [14], pupil diameter (PD) [15], breathing pattern [16], galvanic skin response (GSR) [17], emotion [18], voice intonation [19] and body pose [20] are observed, which, unlike measuring stress hormones, can be acquired through non-invasive means. This paper concentrates on non-invasive and automated methods requiring shorter time periods for detecting and analysing stress. Physiological (e.g. heart rate, skin conductivity) and physical (e.g. facial expressions, voice intonation, body poses, and gestures) features enable such methods and can be used to model stress objectively.

In this paper, a measure of stress refers to a primary (or symptom) measure (or signal) for stress, monitoring stress means examining fluctuations in primary measures for stress, and indication or detection of stress refers to certain fluctuations in primary measures for stress that show an increase in stress towards distress. These terms will be used in the survey to describe work done in literature.

We coin the term *computed stress* and define it as the stress computationally derived from instantaneous measures of stress symptoms obtained by non-invasive methods. A computational model of stress will take some combination of stress symptom measures as inputs to produce a *computed stress measure* as an instantaneous measure of stress at that point in time.

The literature suggests stress is defined as a self-reported measure (e.g. self-assessment [21,22]) or observer-reported measure (e.g. human behaviour coder [23]). These reported measures are used to support stress measures drawn from directly measuring stress symptoms, but do not give an instantaneous stress measure.

The key differences in our approach is that we assume there is an underlying property called stress for which both the symptom measurements and the reported measures are approximations, and that we can use both these sources of information in AI models to learn the underlying model of true stress. Henceforth we use our term, *computed stress*, and distinguish it from the traditional overall stress measure. With our *computed stress*, stress cannot only be compared across time but also across multiple individuals. A consequence of our model is that the *computed stress* will be statistically more reliable than individual reporting or symptom measures.

Stress research has a wide range of potential applications including the capacity to improve personal, government and industry operations, including increasing the robustness of military operations, law enforcements, athlete performance [24], games and education software, life support systems and commercial products. It also has the potential to improve learning and increase work productivity [25]. Computer systems using non-invasive techniques that dynamically provide indications of stress have been exploited to determine stress in fighter pilots [26], but were obtrusive and do not suit usual flight operations and behaviour. However, less intrusive systems have been developed to detect stress in a range of people including car drivers [23,27,28], computer users [29], army officers [30,31], pilots in flight [31,32], surgeons [33], and surgical patients [34].

The current focus of stress research is in determining ways to measure and monitor stress and is in the early stages of computational modelling. A range of sensors and techniques from various fields, including computer science (e.g. bio-inspired, machine learning, data mining), engineering and statistics, have been applied to stress problems. This survey will investigate sensors for primary measures (physiological and physical measures) of stress and computational techniques used for signal analysis, feature extraction, stress detection and recognition, and computational models used in literature over the recent years, and provides a direction for future research.

2. Measuring stress

Traditionally, stress has been measured using assessment based on humans rating stress levels on some scale (e.g. Relative Stress Scale [35], Fear Survey Schedule [36], Cook-Medley Hostility Scale [37], and Brief Symptom Inventory [38,39]), which are subjective. All these assessments require major human intervention, including manually recognising and interpreting visual patterns (possibly with some support tools) of behaviour in observational studies. Stress experiments that use various sensors to obtain objective measures of stress also use subjective assessment to verify measurements obtained from sensors [23]. Lack of data and insufficient capability of existing modelling techniques forces the activity of measuring stress to include these subjective conventional methods. It is regarded that self-assessment is a good measure of stress [35,37], and this alerts us that more work needs to be done to bring objective methods for measuring stress up to par (if not, even better). So far, work proposing objective measures of stress and using these measures to develop a model has not been coherently reviewed and a purpose of this survey is to bring together the major contributions in the field and provide a foundation for future computational stress research.

Primary measures for stress investigated in this survey are physiological and physical measures. A physical feature or characteristic is defined as a property that humans can see changes in without the need for equipment and tools, unlike physiological features, which require the use of tools that

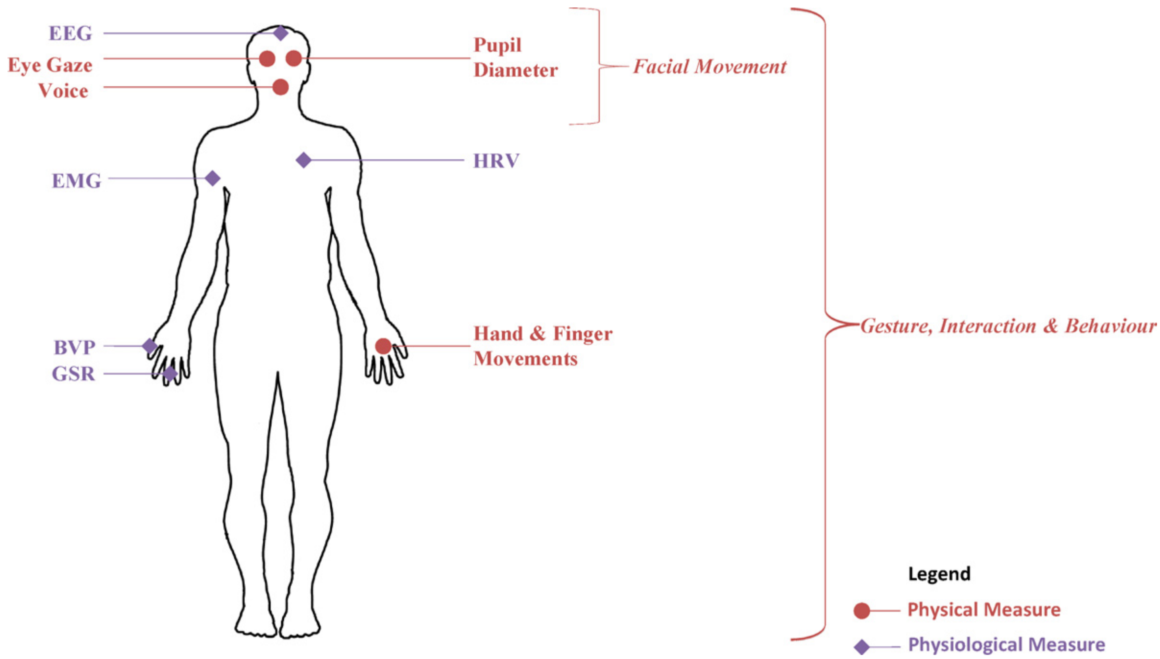

Fig. 1 – Common physical and physiological measures used to detect stress. The figure shows the usual sources for the measures. The measures in this figure are investigated in this survey. The person figure is adapted from [40].

need to be attached to individuals to detect general fluctuations. However, sophisticated equipment and sensors using vision and audio technologies are still needed to obtain physical signals at sampling rates sufficient for data analysis and modelling.

Common techniques for detecting stress include analysing physiological signals, electroencephalography (EEG), blood volume pulse (BVP), heart rate variability (HRV), galvanic skin response (GSR), and electromyography (EMG). In addition, physical signals for measuring stress include eye gaze, pupil diameter, voice characteristic, and face movement. Fig. 1 shows the physical and physiological signals that will be investigated in this survey.

3. Physiological measures

The Autonomic Nervous System (ANS), responsible for involuntary activities, is made up of Sympathetic and Parasympathetic nervous systems. Stressful events or emergency situations cause dynamic changes in ANS, where the activity rate in the Sympathetic Nervous System (SNS) increases and the Parasympathetic Nervous System (PNS) activity decreases. Alternatively, activities in the PNS dominate during resting activities. SNS and PNS regulate the galvanic skin response, heart rate variability, and brain waves, which are the main measures for stress used in literature, and other physiological systems including blood pressure. Details of how stress affects the ANS at molecular and cellular levels are provided in [41]. Note that stress towards distress is not a sole contributor to changes in the ANS and the features it controls, for instance, eustress (which characterises as a positive state, e.g. joy) can elevate skin conductance like distress [42].

Symptoms of stress appear as time progresses and this makes continuous recordings of physiological signals significant to monitor variations and trends to detect stress reliably. In order to deal with voluminous data associated with such recordings, measurements from physiological sensors are usually divided up into segments before features are obtained. In a driving experiment [23], segments were made up of 5 min data out of 30 min, which included rest, city and highway driving representing low, medium and high stress respectively. Main features obtained from physiological data have included normalised mean, root mean square, mean amplitude, variance, and normalised signals. Using feature values over time segments does not only provide data from different perspectives but also helps reduce the effect of noisy or missing data during analysis as opposed to analysing raw signal values.

3.1. *Skin conductivity*

Galvanic skin response (GSR), also known as *skin conductance* or *electrodermal activity response*, is reliable indicator of stress [17,23,43,44]. It is a measurement of flow of electricity through the skin of an individual. When the individual is under stress, skin conductance is increased [45] due to increase in moisture on the surface of the skin, which increases the flow of electricity. Conversely, the skin conductance is reduced when the individual becomes less stressed. Physiological details of the way the SNS affects skin conductance can be found in [46].

The fluctuations in skin conductance are recorded as changes in GSR. Variations in GSR have reflected stress levels in individuals while they played a competitive racing game [47]. In addition, cognitive load [48] and work performance [49],

Table 1 – Analysis of GSR measurement systems.

GSR measurement system	Advantages	Disadvantages
Biopac GSR100C (connected to a computer with AcqKnowledge software suite)	Data transferred to a computer in real-time Allows real-time viewing and analysis of data and trends Raw data is available Sampling rate of 1 kHz	Equipment not portable Sensitive to equipment movement Electrodes are attached to fingers using conductive gel Expensive
Thought Technology FlexComp (connected to a computer with Biograph software suite)	Data transferred to a computer in real-time Allows real-time viewing and analysis of data Waveforms accurate to 500 Hz 2000 samples/s	Equipment not portable Expensive
Thought Technology GSR2	Frequency range from 0 to 40,000 Hz	Does not allow viewing of data in real-time Fingers have to be stably placed on electrode plates for data acquisition Requires RelaxTrace software to upload and view data on the computer
Affectiva Q Sensor	Sampling rate of 2–32 readings/min Portable armband Enables long term data collection Enables real-time data viewing and collection Theoretical characteristics have been reviewed by researchers	Relatively new and lacks usage reviews Expensive
BodyMedia Sensewear	Portable armband Enables long term data collection	Does not allow viewing of real-time data Data is recorded after every minute – this restricts pattern recognition capability for stress detection Main purpose is to assess physical activity with the aim to determine calorie expenditure
BodyBugg	Portable armband Enables long term data collection	Does not allow viewing of real-time data Data recorded after every minute – this restricts pattern recognition capability for stress detection Main purpose is to assess physical activity with the aim to determine calorie expenditure

which can be seen as stressors [50,51], have strong correlations with GSR.

GSR measurement can be taken by measuring electrical potentials between electrodes placed on surfaces of the skin. Electrodes are typically placed on the hand, first and middle fingers. Some popular equipment used in stress related research experiments to monitor GSR include the Biopac GSR100C [47], Thought Technology Limited GSR2 [52], Affectiva Q Sensor [53], BodyMedia Sensewear [54], and BodyBugg [55]. An analysis of the characteristics of these equipments is given in Table 1.

GSR features that require minimal calculations (e.g. mean and sum) have been used for comparing stress in different tasks [48]. More complex features, such as, number of orienting responses in a time segment, sum of the startle magnitudes, sum of the response durations, and sum of the estimated areas under the responses have also been used [56]. However, it is not known whether these complex measures gave better indications of stress than minimal calculations.

3.2. *Heart activity*

Heart rate variability (HRV) is a popular non-invasive measure to detect cardiovascular conditions [57], ANS activities [8], and is another reliable primary measure for stress [13,44,57–59]. Many stress monitoring systems use HRV to detect stress [60,61]. It is believed that HRV also reflects how well individuals are able to adapt to changes [57].

Electrocardiogram (ECG), also known as elektrokardiogramm (EKG), is highly sensitive to heartbeats and a superior measurement for HRV [62]. ECG is a graphical recording of electrical activity produced by an impulse of ions flowing through cardiac muscles, which dissipates into the region around the heart with diminished amounts spreading around the surface of the body. The main electrical signals are produced by cardiac cells depolarising and repolarising. Depolarising occurs due to the flow of ions accompanying atrial heart muscle constriction which results in a P wave. The impulse then travels through the ventricles of the heart causing septal depolarisation, early ventricular depolarisation followed by late ventricular depolarisation. This series forms a QRS wave, the dominant wave. After the completion of depolarisation, ventricular cells repolarise by restoring it to resting polarity, resulting in a T wave. A change in potential can be measured between electrodes attached to a person's body on each side of the heart during the electrical stimulation cycle of the heart. ECG signals are periodic and have persistent features such as R–R intervals, a parameter to determine HRV. The *Einthoven's Triangle*, theoretical triangle area around the heart representing lead vectors, can be used for lead configuration based on desired information. There are three main lead configurations, but Lead I is sufficient to obtain a HRV signal because it gives the complete QRS waveform [63].

Table 2 – Analysis of heart activity measurement systems.

Heart rate measurement system	Advantages	Disadvantages
Thought Technology FlexComp (connected to a computer with Biograph software suite)	Data transferred to a computer in real-time Allows real-time viewing and analysis of data and trends Waveforms accurate to 500–2000 Hz	Equipment not portable Expensive
Biopac ECG100C (connected to a computer with AcqKnowledge software suite)	Data transferred to a computer in real-time Allows real-time viewing and analysis of data and trends Sampling rate of 1 kHz	Equipment not portable Sensitive to equipment movement Electrodes are attached to skin using conductive gel Expensive

Popular systems used to obtain continuous heart rate include the Thought Technology FlexComp and Biopac GSR100C [47]. An analysis of these systems is presented in Table 2.

Acute stress causes the heart to contract with high force and increased frequency. With more chronic stress, the mass of the heart is increased to provide the body with greater response to stressors [64]. A decrease in ECG amplitude is an indicator of stress in healthy individuals [65]. This is due to vasoconstriction, where peripheral blood vessels constrict. Details of how the SNS affects heart activity when an individual is exposed to stressors are presented in [66].

Heart activity has been found to be more correlated with stress as opposed to EMG and respiration recordings [23]. However, the baseline heart rate depends on cardiovascular fitness of an individual and the activity the individual is doing at the time. This means that heart activity measurements cannot be directly compared across multiple people for stress unless measurements are standardised using some baseline measurements.

HRV is an indicator of dynamic and cumulative load making it a good measure for stress. Short term lower HRV reflects acute stress, which means that HRV can be negatively affected during stress [67]. Generally, low frequency (LF) and high frequency (HF) bands of HRV are used to analyse stress. LF and HF are known to reflect SNS and PNS activities respectively. LF has been categorised as 0–0.08 Hz [23], 0.04–0.15 Hz [8,68] or 0.05–0.15 Hz [13,52] and HF has is either in the 0.15–0.5 Hz [13,23] or 0.16–0.40 Hz [52] range. It has been suggested that these definitions for frequency bands could be inappropriate if the respiratory frequencies are not in the range of 0.15–0.40 Hz because it could affect ANS activity estimates [68]. Examples of activities where the respiratory frequencies could be extreme are during intense exercise or during extreme relaxation with respiratory frequencies of 0.7 Hz and 0.1 Hz respectively [68]. The frequency of ECG between 0 Hz and 0.04 Hz, sometimes known as very low frequency (VLF), has been found to distort stress detection [69].

Stress levels are expected to increase with increase in Energy Ratio$_{ECG}$ in Eq. (1) (used as a stress feature in [23,52,70]), which is defined in terms of total energy values in LF and HF:

$$\text{Energy ratio}_{ECG} = \frac{\text{total energy in LF}}{\text{total energy in HF}} \tag{1}$$

A clustering based fuzzy model has been established where HRV features are mapped to a 0–100 (mental) stress scale [8]. Three HRV features, each corresponding to VLF (0.01–0.04 Hz), LF (0.04–0.15 Hz) and HF (0.15–0.5 Hz) bands, were used as parameters to the fuzzy model. The features were defined using continuous wavelet transformations, where detailed definitions are given in [8].

3.3. *Brain activity*

Research shows that relationships exist between brain activity and stress [71,72] and further research is required for more insight to develop models based on brain activity to determine stress. Some methods by which data can be obtained for analysing brain activity are functional magnetic resonance imaging (fMRI), positron emission tomography (PET) and electroencephalography (EEG). Of the lot, EEG is the most commonly used due to high temporal resolution, low intrusive equipment and low cost. EEG has been used to determine stress levels in computer game players [71] and biofeedback games [72].

Neural activity in the brain produces electrical signals, including well known signals that are captured in EEG. EEG records complex electrical waveforms at the scalp formed by action electrical potentials during synaptic excitations and inhibitions of dendrites. Potentials at the scalp range from 20 to 100 μV [73], which can be recorded by pairs of electrodes attached to the scalp (on both sides of the brain hemisphere). The waveforms are characterised by frequency, amplitude, shape and sites of the scalp. Also, age and state of alertness is also relevant to analyse the waveforms [73]. Activities in the right hemisphere of the brain dominate the activities in the left hemisphere of the brain during negative emotions [74], which suggests an area for stress detection. Literature that provides details of the way stress affects the brain include [75].

The potentials can also be measured using less intrusive equipments, such as the Emotiv EPOC headset. An analysis of common brain activity measurement systems is given in Table 3.

EEG signals are categorised by frequency and each category represents some state for a person. The indices, waves or bands in the EEG are categorised in Table 4. Beta and alpha waves represent conscious states whereas theta and delta waves signify unconscious states [76]. Rapid beta wave frequencies (from decrease in alpha wave frequencies) are the main characteristics indicating stress [73,76,77]. Alpha waves appear on both sides of the brain, but slightly higher in amplitude on the non-dominant side, generally observed in people who are right-handed [73]. Band pass filtering can be used to

Table 3 – Analysis of brain activity measurement systems.

Brain activity measurement system	Advantages	Disadvantages
Thought Technology FlexComp Infiniti (connected to a computer with Biograph Infiniti software suite)	Data transferred to a computer in real-time Allows real-time viewing and analysis of data and trends Waveforms accurate to 500 Hz 2000 samples/s	Equipment not portable Expensive
Emotiv Research Edition SDK	Portable headband Less intrusive than conventional EEG caps Allows real-time viewing of data and trends Sampling rate of 128 Hz	Minimal data analysis methods and tools provided with the system Data analysis has to be done offline

remove noise and obtain certain parts and features of an EEG signal before analysis. EEG signals can be filtered using a band pass filter with appropriate values for low and high pass filters, e.g. 30 Hz and 4 Hz respectively.

Brain activity has been examined for those who have experienced chronic stress. It has been found that females with post-traumatic stress have an increased activation in the anterior and middle insula when presented with stimuli that reminded them of the previous stressful events [78]. This characteristic was obtained through fMRI recordings and analysis. In a different study, positive, neutral and negative emotions were classified using EEG [74]. EEG frequency band power, cross-correlation between band powers, peak frequency in alpha band and Hjorth parameters [79] were some features used. Hjorth parameters are time-based characteristics of an EEG signal and details can be found in [79].

Signal processing methods (e.g. FT) have been applied to EEG and analysed in time, frequency and spatial domains. For physical stress [80], ratio of power spectral densities of the alpha and beta bands has been calculated and analysed for stress [81]. Results suggested that the ratios for alpha (r_α) and beta (r_β) powers defined as given in Eqs. (2) and (3) respectively were negatively correlated with self-reports.

$$r_\alpha = \frac{\alpha_R - \alpha_L}{\alpha_R + \alpha_L} \quad (2)$$

$$r_\beta = \frac{\beta_R - \beta_L}{\beta_R + \beta_L} \quad (3)$$

where α_R and α_L in the equations represent alpha bands on the right and left hemispheres of the brain. Beta bands, β, are similarly represented.

Neurofeedback training has been developed to induce stress management by training the brain to reduce symptoms of stress, e.g. Interactive Productline Mindball, a competitive game system. Mindball uses EEG information to assess stress and provide feedback over a period of time, and the player with lower stress levels win the game [77].

EEG signals may have more information about stress levels than blood pressure and heart rate. EEG has been claimed to show differences in relaxation (opposite of stress) levels that blood pressure and heart rate information cannot illustrate [77]. Sum of alpha and theta, and the sum of alpha, beta and theta are good measures [77] for relaxation. It is not yet known whether EEG gives more details of stress than GSR.

Stress states have been classified using EEG data and a decision tree model [71]. Other work has used EEG to classify states that are not directly related to stress but could be used as a basis for further EEG-based stress models. SVMs, ANNs and Bayesian classifiers have not showed much variation in performance for classifying emotions ranging from positive to negative emotions [74]. In addition, EEG data has been used to classify different tasks with ANNs and SVMs and their variance in performance was not significant [82].

Table 4 – EEG wave band categories.

Wave band	Frequency range (Hz)	Individual characteristic(s)
Beta	13–30	Alertness or anxiety
Alpha	8–13	Relaxation
Theta	4–8	Dream sleep or phase between consciousness and drowsiness
Delta	0.5–4	Coma or deep sleep

3.4. *Other primary physiological measures*

Primary measures of stress presented in this section are not reliable if used solely. They are usually used in conjunction with other primary measures investigated above. Apart from stress, there are other body triggers that affect signals of the primary measures investigated in this section by distorting the signals, so it makes stress detection difficult if used as a single measure to detect stress.

3.4.1. *Blood pressure*

Blood pressure (BP) is the pressure exerted on the walls of blood vessels due to blood circulation and varies between a systolic (maximum) and a diastolic (minimum) pressure. An increase BP has been related with increase in stress [83].

Continuous BP waveforms can be measured using systems such as the Ambulatory Blood Pressure Monitor (ABPM-50) or Finapres (FINger Arterial PRESsure) monitor system. Just like traditional BP monitoring systems, ABPM-50 requires a cuff to be wrapped around the upper arm. However, Finapres requires its cuff to be wrapped around a finger and is less intrusive and less disruptive.

3.4.2. *Blood volume pulse*

Blood volume is the amount of blood in a blood tissue during a certain time interval. BVP measures the amount of light that is reflected by the skin's surface. Blood flow through the blood vessels after each heart beat causes changes in light reflections, thus, provides measures for constriction of blood vessels and heart rate. Decreases in BVP have shown to be correlated with increases in stress and lower stress levels have illustrated increases in BVP [84]. Measurements of BVP can be taken using a Photoplethysmography (PPG) from the skin capillary bed of a finger. A PPG bounces infra-red light on the skin and the amount of light reflected provides a measurement of the amount of blood present in the region. It has been used by commercial (HRV-based) stress monitoring systems [85,86]. BVP has been used with other physiological measures to detect stress more reliably [52].

3.4.3. *Electromyogram*

Electromyography (EMG) shows electrical activity produced by active muscles, i.e. muscle action potentials. For stress detection, EMG electrodes have been placed on the trapezius muscle [23], which is located in the shoulder. Other measurements, such as, GSR and ECG, have been found to be better indicators of stress [23].

3.4.4. *Skin temperature*

Skin temperature (ST) in conjunction with other primary measures [29] has been used to measure stress. Investigations show that ST is negatively correlated with stress, i.e. ST increases when stress levels decrease and ST decreases when stress increases [84]. ST has been measured using LM34 IC by placing the sensor on the distal phalanx of the left thumb [52].

3.4.5. *Respiration*

The rate and volume of respiration has been used to measure levels of stress but generally in conjunction with other physiological measures [17]. Most respiration monitoring systems require individuals to wear a belt around their chest [23]. This type of a system is intrusive and may restrict individuals from performing their regular activities. In addition, it has been claimed that other physiological measures, such as HRV and GSR, reflect stress levels to a greater extent than respiration, particularly in driver stress [23].

4. Physical measures

In this survey, a physical feature or characteristic is defined as a property that humans can see changes in without the need for equipment and tools, unlike physiological features, which require the use of tools to detect general fluctuations. Physical signals that are sensitive to stress are behaviour, gesture, body movement, facial expression, eye gaze, blinks, pupil dilation, and voice.

4.1. *Behaviour, gesture and interaction*

Body language can express stress states and humans are generally good assessors at finding these relationships. Body language is defined by body pose and/or body motion. Recognition of body language requires complex techniques that consider degrees of freedom for body configurations and vast variations in motion. Behaviour can be determined by examining body language. Behavioural recognition and analysis requires computer vision techniques with the purpose of understanding a visual environment. However, the common method for determining stress through behaviour is by human experts. Stress levels in car drivers have been assessed by humans who used their judgement to examine driver behaviour on recorded videos [23]. Future research could include developing techniques for automated stress detection from behaviour data. Due to the time-varying nature of stress, HMM, Markov chains, Bayesian classifiers [87], Hidden Semi-Markov Models, ANN, Temporal Scenario Recognition and Petri Nets are some types of techniques that can be investigated for interpreting and analysing behaviour associated with stress.

Stress models based on gesture and interaction features have been quite simplistic. Driving scenarios are rich in stress stimuli that induce drivers to react by gestures, which is an area where stress has been modelled. Gesture recognition has been used to determine stress in car drivers [23]. Approaches for predicting driver behaviour have also been developed through vision based techniques and dynamic Markov models [88,89]. Haptic cues have been used in stress experiments which induces interaction with environments. Investigations with mouse movement show that individuals click mouse buttons harder as their stress decreases [45].

4.2. *Facial features*

Facial features can provide insight to feelings and mental states for individuals including stress. When conversing with an individual, a person can get feedback from facial features which they can act accordingly, e.g. the person might cut a long story short when they observe and realise that the individual is showing signs of frustration, agitation or preoccupation by less nodding, reduced facial muscle movements or frequent eye movements to other objects in the surroundings.

There are systems established (e.g. FaceLAB, NEVEN Vision [90]) that automatically determines facial features (e.g. points on face, head movements, levels of mouth openness) from cameras or videos. Face LAB, a product by Seeing Machines, is a system for head and face tracking and allows obtaining measurements at a sampling rate of 60 Hz for facial features including eye gaze, pupil dilation and blinking signals non-invasively and non-intrusively. The equipment consists of a pair of cameras, with infrared lighting. It does not require any form of contact during signal acquisition.

4.2.1. *Facial expressions*

Stress classification models have been developed from facial feature data and results show that facial expressions can be used to show stress [91]. When responding to stressors, facial expressions indicate biological responses reliably [10], which are commonly used to assess stress. Online analysis of facial expressions can be used to predict behaviour and events, e.g. car accidents, in real-time [92]. Facial muscle movements have been used to determine stress. Increase in head and mouth movements indicate increase in stress [45].

Human observers are good at assessing individuals' stress. The human brain of a healthy individual has facial expression recognition detectors to determine emotions that show symptoms of stress of a person but unfortunately the process by which the brain deduces such conclusions is yet to be understood. Machine learning techniques [93], including SVM, principal component analysis [94], and decision tree-based classifiers [94] have been used for facial expression recognition.

4.2.2. *Eye gaze*

Eyes can provide information in social interaction. Eye gaze provides information on an individual's attention source, and enables deducing the individual's mental states and intentions. Using eyes to focus on a particular object on a computer screen for a greater period of time and frequent focuses on the object are characteristics that correlate with stress levels [45]. The types of measures obtained from eye gaze for measuring stress include gaze spatial distribution and percentage of saccadic eye movement [45].

4.2.3. *Pupil dilation*

Pupil dilation has been examined for stress detection [95]. If an individual's pupil diameter increases [96,97], the pupil dilates at a higher frequency, then it suggests that the individual is possibly in a stressed state [45]. However, both negative and positive stimuli can cause pupil diameters to increase. Results of a research experiment suggested that pupil diameters increased significantly when experiment participants were exposed to negative and positive arousing sounds [15].

A common characteristic used in stress detection are mean values for pupil diameters. An increase in stress has been shown by increasing mean values over a time period [52]. Interpolation techniques have been used to determine pupil diameters during blinks [52], but simple techniques including replacing the blink with the last valid pupil diameter value suffices [15].

Some eye tracking systems used to measure pupil diameters are the FaceLAB 4.5 [98] and ASL-504 eye gaze tracking system [52] with sampling rates of 60 Hz, and Applied Science Laboratories series 4000 eye tracking system with a sampling rate of 50 Hz [15]. The eye monitored for pupil dilation does not seem to be significant but individuals' left eyes are commonly used to monitor pupil diameter [15,95].

4.2.4. *Blink rates*

Eye blinks are sensitive to stress but conflicting characteristics have been suggested for stress detection. Some literatures state that higher frequency of blinks is detected when an individual is under stressful conditions [99] whereas others seem to suggest the opposite [45]. These conflicting conclusions could have been caused by analysing data obtained from different experiment environments. The results of the literature that suggested a correlation between higher frequency of blinks and stress were acquired from real driving experiments whereas the results analysed from solving mathematical tasks on a computer suggested the opposite. In addition, faster eye closure has been suggested as a characteristic for higher stress levels [45].

4.2.5. *Voice*

Stress in voice is defined as "observable variability in certain speech features due to a response to stressors" [100]. Presently, 'certain' is not well defined and the 'features' may include lexical, phonological or prosodic features. Detecting stress in voice is a dynamic process. It is the nonverbal components of voice that reflect stress. Key features claimed to show increases in stress are increases in range and rapid fluctuations in fundamental frequency [101–103], increases in energy for high frequency voice components [104], and greater proportions of high frequency components [19].

Determining stress levels through speech is non-invasive, less obtrusive and less expensive [30] compared to other methods for measuring stress. Such stress monitoring systems are common and have been developed for users including army officers [30], and video game players [105]. Air Force Research Lab (USA) claims that a voice based stress detection system can efficiently measure officers' stress, with the aim to reduce their workload, improve their effectiveness and, as a result, save lives [30]. Stress is part of everyday life and can change the characteristics of speech. Intelligent speech recognition and speaker identification systems use stress models to consider changes in speech characteristics due to stress [106].

Speeches of drivers under stress have been modelled using signal processing techniques, Teager energy operator (TEO) and multiresolution analysis. Dynamic Bayesian networks and hidden Markov models were used to classify the features within utterances. A SVM and an ANN were used to model the features across utterances [107].

Voice features for stress models include loudness, fundamental frequency, zero-crossing rate, jitter and energy frequency ratios [19]. Stress related emotions have been measured in speech by extracting features including voice quality, pitch, duration, intensity, formants, vocal tract cross-section areas, frequency, Teager energy features, glottal characteristics, duration of silence, and speech rate [103,108–110]. A system that detects frustration and annoyance (symptoms of stress) in voice has been developed for flight telephone booking through a prosodic model [109]. Frustration was detected by longer speech durations, slower speech and pitch rates.

Acoustic components in voice that can be used to show stress are caused by physiological changes that depict signs that the human body is responding to stress [19]. This is an example where physiological and physical characteristics of stress are related. Micro-muscle tremors (MMT), caused by muscle tension, and voice stress analysis (VSA) reflect stress. MMT is caused by the muscles in the vocal tract and is transmitted through speech. MMT and VSA have been used in lie detector systems [111].

4.3. *Fusion of measures*

Combinations of sensors have been used to give a better measure of stress. Facial expressions, eye movements, head movements, GSR, RTD and BVP data have been fused to develop a stress model [45]. Physiological sensors have been fused to determine stress. GSR, BVP and HR have been used to determine stress in video game players [49]. Computer users have had their GSR, EMG, ECG and respiration data used for stress classification [95]. Car drivers have had their relative stress levels monitored by ECG, GSR, EMG and respiration recordings, but ECG and GSR mirrored stress more reliably [23]. In addition, drivers have had facial expressions and road

Table 5 – Empirical ranking of primary measures for measuring stress.

Rank	Primary measure
1	HRV
2	GSR
3	EEG
4	PD
5	Voice
6	Eye gaze
7	Facial expression
8	BP
9	ST
10	BVP
11	Eye blinks
12	Respiration
13	EMG

conditions recorded and synchronised to the physiological measures to support results [23]. Computer users have had their HRV, GSR, pupil diameter and ST recordings monitored to detect stress [52].

Other work has involved using physiological measures to model symptoms of stress, e.g. agitation, anger, fear and frustration. HR, GSR and ST have been used to recognise agitation in dementia patients [112]. Emotions of anger, fear and frustration have been classified using GSR, HR and ST [54]. An emotional recognition system has been developed based on EEG, GSR, HRV, BVP and respiration [113].

Some measures in a combination of measures may be redundant with other measures and this may cause collection of unnecessarily large volumes of data and unnecessary processing time. This motivates using an optimal combination of measures for measuring stress. Techniques used for determining an optimal measure combination include mutual information measure [45] and principal component analysis [71].

4.4. *Evaluation of primary measures for stress*

Table 5 provides an empirical ranking of primary measures for measuring stress based on discussion in this report, their correlation with stress claimed in literature, equipment intrusiveness, techniques developed for mapping to stress scales, and extent of usage in the literature.

Accurate features from physical measures can be deduced without attaching sensors on an individual through equipments such as FaceLAB and microphones. However, physiological measures have been widely used for stress detection even in stress monitoring systems, which require individuals to wear or touch electrodes or sensors. Potential area of research could be to develop stress detection techniques using physical measure features sufficiently powerful so that individuals are not required to make contact with equipment.

5. Published stress data sets

A data set for automobile drivers in different stress driving conditions, consisting of physiological measures (ECG, EMG, GSR and respiration), have been published and details are in [23]. The data set is available at http://www.physionet.org/pn3/drivedb/.

6. Stress monitoring systems

Commercial biofeedback systems (e.g. ThoughtStream [114], StressEraser [60], emWave [61]) that provide continuous feedback have been developed to assist with managing stress. The ThoughtStream system bases stress monitoring on GSR, while StressEraser and emWave use HRV. Both, StressEraser and emWave use a PPG sensor to monitor consecutive blood pulses in a finger and directs the user to breathe in certain patterns to reduce stress [85,86]. To lower stress levels using the ThoughtStream system, the user listens to music where its tone is controlled by the user's GSR readings. There are similar systems, e.g. Procyon [115] and Proteus, developed by Mindplace [116], the same manufacturers as the ThoughtStream system, which extend the ThoughtStream system to incorporate visualisation tools with visual material synchronised with music.

7. Stress scale

We can classify stress by “Very Stressful”, “Stressful”, “Somewhat Stressful”, “OK”, “Somewhat Calm”, “Calm”, and “Very Calm”. Stress in computer users has been classified as “Stressed” or “Relaxed” [52]. Similar labels have been used for stress in computer game players, e.g. “No-Stress”, “Average” and “High-Stress” [71]. Stress levels in car drivers have been classified into three different categories – low, medium and high [23]. Data segments for low-stress were taken from rest periods, medium-stress segments were taken from uninterrupted highway driving, and high-stress segments were taken from busy main street city driving. Due to the uncertainties, the categories could be defined in terms of fuzzy sets. Future research could propose standard categorical labels for stress that following research can adopt.

Alternatively, stress measure can be defined on a continuous scale. A continuous scale for mental stress has been defined as 0–100, where higher values represent increase in stress levels [8]. Stress measure could be represented on a time-varying scale where each time step has an associated stress measure, which could be used to summarise stress characteristics over time.

8. Feature extraction techniques

Various signal processing techniques have been used to extract features from primary nonstationary signals of stress. Popular techniques include Fourier transformations (FT) and Wavelet transformations (WT). They can be used to remove noise in time series or feature extraction [99,117]. It is common to transform physiological signals (e.g. EEG [99], GSR [23] and HRV [62]) from time to frequency domain in order to extract features that are more apparent in the frequency domain for analysis using FTs. WT is another technique that allows signals to be transformed from time to frequency domains, but allows data to be divided up into different frequency components. Unlike FT, WT performs well when approximating data that has sharp spikes and discontinuities.

Principal Component Analysis (PCA) and Independent Component Analysis (ICA) have mainly been used to extract features from EEG data but can be used for reducing the feature set or removing unwanted features from the set of primary measures for stress models. PCA was used to reduce features in EEG signals to model stress [71]. ICA has been used to remove eye movement and other muscular movement information, which is generally considered to be noise, from EEG signals [82].

9. Computational techniques

Various software programs, tools and packages (e.g. Matlab [118], AcqKnowledge [119] and Biosignal Analysis Software [58]) are available for analysing physiological and physical signals. Most of the tools and applications are not specifically designed for primary measures of stress but they suffice for general data exploration. Exploring signal data is beneficial because it enables selection of appropriate computational techniques to model stress. It also allows detection of noisy, corrupted or missing signal data, which is useful in the process of preparing data before computational stress models are developed. This section focuses on computational modelling techniques used for stress.

9.1. *Bayesian classification*

Bayesian classifiers can predict class membership probabilities for given samples. Such classifiers are based on Bayes' theorem and have been used to calculate posterior probabilities stress states. Naive Bayesian classifiers have been used to classify stress [52,95], which assumes classes are independent. A maximum posterior (MAP) decision rule was used to classify features from physical measures to stress classes: "Stress" and "Normal" [52]. Alternatively, Bayesian belief networks or Bayesian Networks (BN) can be used when classes have dependencies. A BN can be represented by a directed acyclic graph or conditional probability tables to show joint conditional probabilities for attributes or variables. Nodes in the graph depict variables and arcs portray causality. A Dynamic Bayesian Network (DBN) has been used to model stress [45]. Unlike a traditional BN, a DBN can show how properties of stress vary over time.

9.2. *Decision trees*

Decision tree classifiers, based on a *divide-and-conquer* approach, have been used in stress classification. The structure of a decision tree is like a flowchart. Each internal node represents some criteria or test to divide the input space into regions, each branch denotes an outcome of the test, and each terminal node or leaf represents a target class. Algorithms have been established to generate decision trees [120]. Unknown samples are classified by starting at the root of the tree and moving the sample towards the leaf after testing the sample against the criteria at the internal nodes in the path.

Decision trees have been used to classify stress based on characteristics in physiological measures (e.g. EEG [71]) and combinations of primary measures (e.g. combination of BVP, GSR, PD and ST [52]). A potential problem with using decision trees to model stress is the crisp splits for prediction. Future research could investigate softening the decision process with the use of fuzzy techniques or some probabilistic framework.

9.3. *Artificial neural networks*

Artificial neural networks (ANNs) are inspired by biological neural networks with characteristics for learning and reacting, making them a common technique in classification problems in health systems and an upcoming approach for stress research. Stress models based on ANN are at the early stages of research and have produced promising results. It has been claimed that an ANN is better at recognising stress than humans from voice recordings [105] and this result contributes to motivation for further research with ANN for stress.

Multi-layered perceptrons, a type of ANN with multiple hidden layers, have been used for stress classification [121]. Features from physiological measures were used in the classification. Recurrent ANNs (RANN) have been used to measure stress. A RANN is an ANN that contains feedback connections. It has been claimed to be useful for retaining information of how the previous sample was processed to process the current sample effectively. A RANN based on labelled voice data for experiment participants playing a video game has been developed [105]. Utterances were recorded when participants answered questions while playing the video game.

Choosing the number of hidden neurons and layers is a critical aspect in defining the structure of an ANN. With a small number of hidden neurons, an ANN will not be able to differentiate between complex patterns, which will result in an underestimation of the actual trend. On the other hand, a large number of hidden neurons could lead to a poor generalisation because of over-parameterisation. The number of hidden neurons is usually obtained empirically. In some situations the accuracy may be similar for different topologies, for instance, the accuracy for the one and two hidden layers were similar when classifying fatigue [122].

9.4. *Support vector machines*

Stress models have been developed using support vector machines (SVMs). It can be used for classifying linear and non-linear primary measures. A SVM transforms training data to a higher dimension, in which a linear separating hyper-plane is determined. An appropriate non-linear mapping can separate two classes of data with a hyper-plane provided that the data has been transformed to a satisfactorily high dimension. Training samples, or *support vectors*, and *margins*, which are defined by support vectors, are used to determine a hyper-plane. SVMs have been used to predict stress states using BVP, GSR, PD and ST data [29,52].

Other research has modelled properties more related with the symptoms of stress. SVM has been used to recognise agitation in dementia patients based on physiological signals: HR, GSR and ST [112], which is somewhat related to stress research. It was claimed that their SVM algorithm was not dependent on experiment subjects. SVM has been used to model emotions based on EEG data [74].

9.5. *Markov chains and hidden Markov models*

The Markov property is a time-domain process with conditional probability density of the current event depending on the ith most recent event, given all the past and present events. A Markov chain is the simplest form of a Markov model. It models the state of a system with a random variable, which varies with time, where a state is dependent on prior states. The system of a Markov chain is fully observable. On the other hand, a hidden Markov model (HMM) is a type of a Markov chain but, as its name suggests, it is partially observable. Only the sequence of observations can be seen in HMMs. HMMs are a double stochastic process with a Markov chain that has a finite number of states and a set of functions that corresponds to each state. The process is in one state in the system at a time and produces a symbol that is dependent upon a random function for that state. The generalised topology of a HMM is a fully connected structure where a state can be reached from any state.

In stress research, HMMs have been mainly used in recognising stressed speech [106,107,110,123]. HMMs have been used for modelling emotions from voice data as well [124]. Markov models, including dynamic-based and HMM, have been used for behavioural recognition and prediction [89].

9.6. *Fuzzy techniques*

Fuzzy-based techniques, in particular fuzzy clustering have been used to measure stress. A fuzzy technique has used HR to model workload [125], which is somewhat related to stress. In addition, fuzzy filters could be used to filter out uncertainties in physiological measures of stress. A nonlinear fuzzy filter for reducing random variations has been developed for heart rate signals [126].

Fuzzy clustering, a hybrid of fuzzy and clustering techniques, has been used to determine stress based on HRV as a primary measure [8]. Unlike traditional clustering where data elements belong to at most one cluster, fuzzy clustering generates data clusters such that data elements can belong to more than one cluster with different membership degrees. Each data element has a set of membership level values.

9.7. *Combination of techniques*

Hybrid techniques for stress models include an adaptive neuro-fuzzy inference system [18], a fuzzy clustering technique [8], and a technique combining WT and ANN [117]. However, the number of hybrid techniques developed for stress models are few and, in relation to the previous sections in this report, there is scope for more hybrids. On the other hand, primary measures have been modelled using many more types of hybrid techniques but not directed to stress, e.g. models of behaviour [87] and emotions [127]. A BN and a HMM was fused for behavioural analysis and recognition [87]. They used behavioural analysis to discover criminal activities by using scenes around the airport, e.g. unloading baggage. An extension of this research could include determining whether an individual is stressed by analysing their behaviour, e.g. interviewee jitteriness during an interview.

Table 6 – Rankings of techniques used for modelling stress.

Rank	Modelling technique	Reported accuracy	Inputs for model
1	SVM	90.10% [52] 79.3% [18]	GSR, HR, PD, ST EMG, ECG, Respiration, GSR
2	Recurrent ANN	MSE = 0.084 [105]	Voice
3	Adaptive neuro-fuzzy system	76.7% [18]	EMG, ECG, Respiration, GSR
4	ANN	82.7% [113] Not provided	EEG ECG
5	HMM	Not provided	Voice
6	Decision tree	88.02% [52]	GSR, HR, PD, ST
7	Naive Bayesian network	78.65% [52]	GSR, HR, PD, ST
8	Fuzzy clustering	Not provided	HRV

9.8. *Evaluation of techniques for modelling stress*

Not many comparisons have been done to evaluate stress models. In an investigation for performance of stress models based on supervised learning, SVM was claimed to be a superior technique to Naive Bayesian and decision tree classifiers [52].

Table 6 presents an empirical ranking of techniques used for modelling stress based on the discussions in this report, comparisons and usage in literature.

Models of stress in literature have used their own methods for measuring stress and determining performance. Despite the differences in metrics, the models have performed much better than chance, which suggest that stress can be successfully modelled and that further research in this area will have an impact for modelling stress.

10. Summary and future work

Stress has been identified as a serious and growing issue adversely impacting both individuals and society, and stress recognition and classification (or prediction) research can lead to solving the stress problem. Some benefits arising from automated stress recognition and classification include improvement in education, driving and work productivity.

Stress cannot be directly measured but it can be determined by certain characteristics in primary measures. Primary measures have been considered in isolation or in some basic combination. Appropriately collected and collated physiological and physical signals can be used to measure stress, which requires consideration of aligning multi-source signals. Future work could involve investigating and modelling latencies for physiological and physical signals for fusion of primary measures for measuring stress and the use of techniques such as dynamic time warping to find an optimal alignment.

Based on literature investigated in this survey, there has not been an extensive use of combinations of physical and physiological sensors in research yet where stress can be monitored through social and emotional interactions. Physiological sensors can detect stress to some extent and usually fulfils its purpose but they can be somewhat cumbersome. There are occasions and cultures where it may be inappropriate to attach sensors to people, which is a drawback. On the other hand, some physical sensors require less or no contact at all and have the capability of detecting stress, but more research is required before it can be comfortably said that physical sensors are as good as, if not better, than physiological sensors in measuring stress. Combining the two different types of sensors and analysing their impact could be a starting point to determine the relationship and dissimilarities in the functionalities. It will also provide a rich method of analysing communication, both social and emotional, between any combination of people and intelligent systems.

Clustering approaches can be used for objectively grouping of unlabeled data (including data in time or frequency domains) for primary measures to determine stress categories. It can also be used to determine data outliers. Clustering algorithms that have been established to determine clusters have been generally categorised as *partitioning methods* (e.g. *k*-means), *hierarchical methods* (e.g. BIRCH), *density-based methods* (e.g. OPTICS), *grid-based methods* (e.g. WaveCluster), and *model-based methods* (e.g. Self Organising Maps) [120]. For determining stress levels, clustering of data for primary measures would be more suitable if a categorical (including an interval-based) scale for stress is used. Clustering techniques can be included in the process for determining an optimal combination of primary measures.

Models developed to date that describe stress are quite simplistic. Generally, established techniques such as ANN and SVM have been used to model stress. Novel or more complex computational techniques are needed for stress models.

Future stress models could be developed based on models developed for similar research problems e.g. models for emotion [128] and mental workload [129] (which have been based on physiological signals, e.g. EEG, HRV and GSR, and these signals are based to detect stress). In addition, fear and anger are some emotions that are symptoms for stress so models for stress and emotions may overlap. Genetic programming (GP) techniques have been used for determining emotions. A GP has been used to generate regression equations from facial expressions to measure emotions [130]. In addition, genetic algorithms have been used for feature selection in EEG for developing emotion models to reduce computational resources required for an Elman network [113], a type of recurrent ANN. These techniques are examples of some techniques that can be used in stress research.

Conflict of interest

None.

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